Analysis of Gauge-Measured and Passive Microwave Derived Snow Depth Variations of Snowfields

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Popular Summary

Remote sensing of snow depth has been used to infer snow depth for many years. Passive microwave remote sensing of snow depth is compared with the snow gauge data.

Statement of Significance

Passive microwave remote sensing of snowfields has been used for many years. However the accuracy of the retrieved areal snow depth is not known. This paper statistical analyzes the snow gauge data (about 350 gauges) in the Northern Great Plains of US and SSM/I derived snow depth. We found that with one gauge within 10,000 km^2 the sampling error is about 20 cm, while the passive radiometer the error is about 10 cm.

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Abstract

Accurate estimation of snow mass is important for the characterization of the hydrological cycle at different space and time scales. For effective water resources management, accurate estimation of snow storage is needed. Conventional snow gauges measure snow depth at a point and in order to monitor snow depth in a temporally and spatially comprehensive manner, optimum interpolation of the points is undertaken. Yet the spatial representation of point measurements at a basin or on a larger distance scale is uncertain. Space-borne scanning sensors, which cover a wide swath and can provide rapid repeat global coverage, are ideally suited to augment the global snow information. Satellite-borne passive microwave sensors have been used to estimate snow depth (SD) with some success. The uncertainties in point SD and areal SD of natural snowpacks need to be understood if comparisons are to be made between a gauge SD and satellite

SD. In this paper we address three issues relating satellite estimates of SD and ground measurements of SD in the Northern Great Plains of the USA, from 1988-1997. First, it is shown that comparing samples of ground measured point SD data with satellite-derived 25 x 25 km pixels of SD, there are significant differences in SD values even though the accumulated data sets showed similarities. Second, from variogram analysis, the spatial variability of SD from each data set was comparable. Third, for a sampling grid cell domain of 1° x 1° in the study terrain, more than 10 distributed snow gauges per cell are required to produce a sampling error of 5 cm or better. This study has important implications for validating SD estimates from satellite microwave observations.

I. Introduction

With the continued growth in world population and industry development, demands on global water resources have increased greatly. For effective water resources management there is a need to accurately quantify the various components of the hydrological cycle at different space and time scales. Snow is a renewable water resource of vital importance in large parts of the world and is one of the major hydrological cycle components. It is also a major source of global water storage and runoff. For example, in the western U.S. snow contributes over 70% of total water resources. In order to better predict snow storage and detect trends in the variations of water resources, accurate snowpack information with known error characteristics is necessary.

Traditionally, rulers, fixed snow stakes, and snowboard gauges are used to measure the snow depth (SD) at a point. In general, point measurements of SD produce high quality data representative of a small location (< 10m scale length). In order to monitor SD in a temporally and spatially comprehensive manner, optimum interpolation of the points must be undertaken. However, the spatial representativity of point measurements in a basin or at larger scale is uncertain (Atkinson and Kelly 1997). Furthermore, the spatial density of SD measurements in most parts of the world is rather low; thus, the accuracy of spatially-integrated point measurements of SD needs to be carefully assessed.

Space-borne scanning microwave sensors, which cover a wide swath and can provide rapid repeat global coverage are ideally suited to augment global snow information. For example, passive microwave radiometers such as the Scanning Multi-frequency Microwave Radiometer (SMMR) on Nimbus-7 and Seasat-A, and the Defense Meteorological Satellite Program (DMSP) Special Sensor Microwave/Imager (SSM/I) have been utilized to retrieve global SD. In order to assess the representativeness of satellite-derived SD, it is necessary to determine how and whether the point gauge SD measurements can be compared with the space-borne estimated SD that typically represent about 25 km by 25 km in area.

The uncertainties in point and areal SD measurements of natural snowpacks need to be understood if comparisons are to be made between a gauge SD and satellite derived SD. The statistical variability of the snow depth, as represented by the variogram, has a direct effect on the accuracy of the snow validation. Consequently, it is essential that the magnitude and cause of any variability is clearly defined for robust global validation of satellite-derived SD estimates. In this paper we use sparsely distributed snow gauge data from the National Weather Service (NWS) Cooperative Station Network and SSM/I-derived SD estimates to study the large-scale snow distribution.

To understand the snow distribution characteristics from gauge measurements, it is necessary to know the gauge density and the defined SD areal accuracy. Geostatistical analysis can be used to gain a better understanding of the spatial variability of snow depth in large areas, such as river basin size of the Northern Great Plains. Although there are large portions of the world where the spatial density of gauges is less then 1 per 10,000 km^2 (approximately the area of one degree latitude by one degree longitude), the aims of this study are to understand and quantify statistically the uncertainties associated with sparse sampling of SD over a regional scale, and to determine how these uncertainties affect the validation of global SD estimation from satellite observations and to find out how well remote sensing-derived SD can be validated by current gauge data, specifically:

1) how well does gauge SD compare with satellite derived SD?
2) what are the characteristics of snow spatial distribution? and
3) what are the required sampling characteristics of snow gauge measurements that can enable the validation of satellite-derived SD, given a pre-defined accuracy requirement?

II. Background

Any remote sensing technique that can estimate accurately snow storage is of great benefit for global water cycle research and water resources applications. With space-borne satellite sensor data, global snow measurements can be achieved. Space-borne sensors can image the Earth with spatial resolutions varying from tens of meters (e.g. visible and infrared spectrometer, synthetic aperture radar) to tens of kilometers (e.g.

passive microwave radiometers). Visible and infrared sensor applications to snow are limited to clear sky occurrences and are sensitive only to snow surface properties, while passive microwave sensors are solar illumination independent and are sensitive to snow volume properties. Both remote sensing approaches have been used to monitor snow covered areas. With the improvement in satellite instrumentation, regional and local scales can now be mapped effectively. Passive microwave sensors have been used to monitor continental-scale snow cover area extent in the Northern Hemisphere for several years (Chang *et al.* 1987). However, passive microwave retrieval methods of snow water equivalent (SWE) and/or SD are less mature than VIS/IR sensor mapping approaches, and often resulting in large uncertainties from retrievals at the global scale.

Microwave brightness temperature measured by space-borne sensors originates from radiation from 1) the underlying surface, 2) the snowpack, and 3) the atmosphere. The atmospheric contribution is usually small at microwave frequencies and can be neglected over most snow-covered areas, especially at higher latitudes. In this paper, therefore, we neglect the atmospheric effects when extracting snowpack parameters. Snow crystals within snowpacks are effective at scattering upwelling microwave radiation and the microwave signature of snowpack depends on both the number of scatterers and their scattering efficiency. The degree of scattering is frequency dependent with higher frequency (shorter wavelength) radiation scattered more than lower frequency (longer wavelength) radiation. The deeper the snowpack, the more snow crystals there are available to scatter microwave energy away from the sensor. Hence, microwave brightness temperatures are generally lower for deep snowpacks, with a larger number of scatterers, than they are for shallow snowpacks, with fewer scatterers (Matzler 1987;

Foster *et al.* 1997). The scattering effect increases rapidly with grain size, and the formation of death hoar, large snow crystal occurs in thin snowpacks subject to cold air temperature. This can result in very strong signals from thin snowpacks, as observed by Josberger *et al.* (1996) in a comparison of microwave observations and snowpack observations from the Upper Colorado River Basin. Based on radiative transfer theory, Chang *et al.* (1987) successfully developed a method to estimate SWE using SMMR observations. SSM/I data have been used routinely to infer the SWE in many areas of Canada (Goodison and Walker 1995). Derksen *et al.* (2002) found that the time series of SSM/I SWE remains within 10 to 20 mm of surface observations in the Canadian prairies. Walker and Silis (2001) reported estimated snow cover variations over the Mackenzie River basin. Their algorithm was tested using "ground truth" in-situ data and shows that the inferred SWE estimates generally underestimate the measured SWE by between 10 to 30 mm. The derivation of an accurate algorithm is complicated by the snow crystal metamorphism that occurs through the winter (Hall *et al.* 1986). To model this effect, Josberger and Mognard (2002) and Mognard and Josberger (2002) developed an algorithm for the U.S. Northern Great Plains that includes a proxy for crystal growth based on air temperature. Kelly *et al.* (2003) coupled a spatially and temporally varying empirical grain growth expression with a radiative transfer model to estimate SD in the Northern Hemisphere. All of these results encourage us to study further the interaction of microwaves with snow parameters to derive a validated algorithm with known errors.

Ideally, it is recognized that SWE is more closely related to the water resources stored in a basin. However, global SWE data sets are not available, rather SD is the quantity that is recorded at many weather station locations. SD is measured at a point, usually from a ruler or snowboard gauge. In the high latitudes the distributions of liquid precipitation (rain) and solid precipitation (snow) are very similar. Rain gauges have also been used to record accumulated snowfall although such devices are often subject to large uncertainties. Rain gauges are also sparsely distributed around the globe with large regional variations in spatial density. For example, in Germany there may be 3-5 stations in a 25 by 25 km^2 area (Rudolf *et al.,* 1994). In the USA there are some areas with one station in 25 by 25 km^2 while in some areas of Russia, for example, typically there is only one station in area 100 by 100 km^2. Snow courses provide more detailed measurements of snow parameters located at discrete sites along a defined transect. However, they are even sparser in occurrence. Thus, with SD gauge measurements more readily available for comparison with satellite estimates, gauges are the prime validation source used in this study. Also, since SD is the most widely measured variable, we use the SD form of the microwave retrieval algorithm from Chang *et al.* (1987) in this study.

III. Snow Field Descriptions and Data Used in the Study

The Northern Great Plains (NGP) study region covers a geographical area from 42°N to 49°N and 91°W to 104°W. The test area is about 800,000 km^2. This encompasses the states of North Dakota and South Dakota and Minnesota. The geomorphology of this area is rather homogeneous. For example, the Roseau River in Minnesota and Manitoba (10,000 km2), flows into the Red River of the North. The Roseau basin has low relief (< 500 m) and has a mixture of cropland and forests (hardwoods and conifers). Recently Josberger *et al.* (1998) reported a comparison of the satellite and aircraft remote sensing SWE estimates in this region. They found that in this prairie ecosystem passive microwave observations could be used to estimate SWE. This area, therefore, is ideal for studying the relationship between snow gauge measurements and microwave estimated snow depths.

SD retrievals were performed using observations from SSM/I instruments aboard Defense Meteorological Satellite Program (DMSP) F-8, F-11 and F-13 platforms. Gauge snow depth measurements, archived by the U.S. National Weather Service (NWS) and obtained from the co-operative network of observers were collected for the study region. These ground measurements consist of daily weather observations of temperature, precipitation, snowfall and snowpack thickness at about 350 stations in the area, although this number varies from year to year. Typically, the snow depth information is collected daily but with a long time lag before the data become available. Figure 1 shows the location of the snow gauge data within the NGP study region. All data were georeferenced to the Equal Area Scaleable Earth grid (EASE-grid). The SSM/I data were obtained from the National Snow and Ice Data Center (NSIDC) in 25 x 25 km EASE-grid projection (Armstrong and Brodzik 1995). With the exception of 1994, our analysis focused on the average of three days (10-12 February) for each year of 10 years (from 1988 to 1997). This averaging process ensured complete coverage of the study region for the selected date. In 1994, because of incomplete SSM/I coverage, the 3-day average was shifted to 27-29 January. These three days were chosen since they represent a time in winter when the snowpack is potentially at its most stable and extensive, with minimal liquid water content. By undertaking the analysis for the same time in consecutive years, potentially consistent biases in the data (either satellite or ground) are more likely to be identified.

IV. Data Analysis

(1) Comparisons of gauge SD measurements and single passive microwave SD estimates

Statistical analysis of both the gauge SD and SSM/I SD, for each of the ten years (from 1988 through 1997) and the ten-year composite show that the SSM/I estimates generally compare well with the gauge measurements. Table 1 gives summary statistics for each year plus composite averages. The mean gauge SD is highly variable from year to year (1.5 cm to 45.4 cm). In the ten-year period, there were 3 years when SD was less than 10 cm, five years when SD was between 10 cm to 30 cm, and two years when SD was greater than 30 cm. The corresponding range of SSM/I estimated mean SD (1.7 cm to 43.4 cm) was very similar to the gauge measurements, with the total composite mean SD from SSM/I estimates almost identical to that of the gauge data. The correlation between average yearly gauge and SSM/I SD values for the period is 0.83.

Differences of the gauge SD and SSM/I derived SD varies from year to year. The maximum difference of the means was 18.4 cm (1994). For 1996 the minimum difference of the mean was found to be 0.1 cm. Generally, there is a greater variation of snow depths observed for the gauge data that the satellite derived estimates. This is expected since the variability of snow at a point tends to be greater than that observed for a footprint which is a smoothed, integrated signal from within an instantaneous field of view. A statistical hypothesis test, the paired *t*-test, was used to determine whether or not there were significant differences between the gauge and SSM/I derived SD. The paired *t* statistic (*t*) is defined as

$$t = \frac{\mu}{(\sigma / n^{\frac{1}{2}})}, \qquad (1)$$

where μ and σ are the mean and standard deviation of the paired differences of the two variables (gauge SD and SSM/I SD) and n is the number of data pairs. For $n > 30$ t follows approximately a normal distribution (in this case n > 250). The hypothesis of difference is rejected if $|t| < 1.96$. The paired t-statistics are included in Table 1. Inspection of the t values shows no systematic pattern from year to year. There are seven years with $|t| > 1.96$ and three years (1990, 1996 and 1997) with $|t| < 1.96$. For those years where the value of t is larger than 1.96, there are a significant difference between the gauge SD and SSM/I derived SD at the 95% level confidence. The t-test value is -0.04 for the composite ten year data set. The mean difference between the gauge SD and satellite SD is 0.17 cm. The standard deviation of the difference is 18.4 cm, which is slightly larger than both the accumulated gauge and SSM/I snow depth means (17.2 cm and 17.4 cm, respectively). This was expected and reflects the difference between point and areal estimation modes.

Gauge measurement error is an important factor explaining why gauge and satellite data have different statistical characteristics. Snow depth measured at a gauge reflects snow accumulation subject to local micro-scale processes, while SSM/I-estimated snow depth reflects average snow conditions, subject to controls at the local to regional scale. For example, wind speed is the most important environmental factor contributing to the under-measurement of snow at a point (Goodison *et al.* 1989). In the NGP region, frequent high wind speed is common and causes a system bias error. At cooperative stations typically snow rulers or snowboards are used to measure SD. To obtain a representative SD measurement of new snow under drifting conditions, careful judgment by the observer is required.

(2) An assessment of the spatial variation of gauge and passive microwave snow depth

Large spatial and temporal variations exist in global and local snow cover extent and volume (Frei and Robinson 1999). Errors of these variations are not very well understood, although it is important for better climate observation. It is necessary to better understand the spatial characteristics of different scales of SD. Jacobson (1999) defined five spatial scale lengths of weather parameters: planetary scale (> 10,000 km), synoptic scale (500 to 10,000 km), mesoscale or regional variation (2 km to 2000 km), microscale (2mm to 2 km), and molecular scale (< 2mm). In the NGP study region, we are concerned with the characterization of snow distribution at the microscale and mesoscale.

From the t-test values of the previous section, mesoscale (SSM/I) and microscale (gauge) comparisons of snow depth revealed that for seven out of the ten years, significant differences existed between these two data sets. However, when the data were aggregated over a longer time period (ten years), the $|t|$ value was less than 1.96 suggesting that overall the two data sets are not significantly different. To further understand this characteristic, analysis of the spatial variability of the two data sets was undertaken.

The variogram, the central tool of geostatistics, can be used to examine the spatial dependency of a variable. It provides an unbiased description of the scale and pattern of spatial variation. Observations of a selected property are often modeled by a random variable and the spatial set of random variables covering the region of interest is known as a random function (Isaaks and Srivastava 1989). A sample of a spatially varying property is commonly represented as a regionalized variable, (e.g., as a realization of a random function). The semi-variance (γ) may be defined as half the expected squared difference between the random functions Z(x) and Z(x+h) at a particular lag h. The semi-variogram (hereafter referred as variogram), defined as a parameter of the random function model, is then the function that relates semi-variance to lag:

$$\gamma(h) = 1/2\ \mathrm{E}[\{Z(x)-Z(x+h)\}^2], \tag{2}$$

where E is the ensemble average of pairs. The sample variogram γ(h) can be estimated for p(h) pairs of observation or realizations, $\{Z(x_l+h), l=1,2,\ldots p(h)\}$ by:

$$\gamma(h) = 1/2p(h)\sum_{l=1}^{p(h)}\{Z(x_l) - Z(x_l + h)\}^2 \tag{3}$$

A mathematical function or model is usually fitted to the experimental values, which are discrete, to represent the true variogram of the region, which is continuous. The experimental values are often erratic because they are subject to error. In general, the variogram model is either unbounded (increases indefinitely with lag) or bounded (increases to a maximum value of semivariance, known as the sill, at a finite positive lag, known as the range a). The sill is equal to the *a priori* variance (that defined for an infinite region) of the random function (RF), while the range indicates the limit to spatial dependence, beyond which data are statistically uncorrelated. Often the model approaches and intercepts the ordinate at some positive value of semivariance known as the nugget variance c_0. The nugget variance results from measurement error (Atkinson, 1993), the uncertainty in estimating the variogram from a sample, the uncertainty in model fitting, and spatially dependent variation acting at scales finer than the sampling interval. The structured component of variation c_1 is then the sill minus the nugget variance, so that $c_0 + c_1 =$ sill.

For each data set, variograms were computed for the gauge and SSM/I data. As an example, Figure 2 shows the variograms with spherical models fitted for the gauge data and the SSM/I estimates for 1988. Authorized models were fitted to all experimental variograms using a least squares criterion with the exception of the gauge data for 1990 and 1991 when the experimental variograms were unbounded. The reason for the lack of structure for these two years is probably because there was so little snow accumulated at the stations (averages of 1.8 and 1.5 cm). These averages are substantially comprised of 0 cm measurements such that very little spatial variation was present. For two data sets (1996 gauge and 1997 SSM/I), data were de-trended using first order polynomials; this was because a trend in the data produced unbounded variograms. Unlike the 1990 and 1991 data for the gauge measurements, appreciable snow accumulation was present in both 1996 and 1997, and clear direction snow accumulation gradients were present (NE to SW in the case of the 1996 gauge data and NW to SE for the SSM/I estimates).

The main parameters of interest for the comparative analysis were the nugget variance and the range. Variograms were computed using GSTAT software (Pebesma and Wessleing 1998) and estimated to a maximum lag of 1000 km. Spherical variogram models were fitted to the variograms using the weighted least squares criterion. Table 2 shows the model ranges and nugget variances for the gauge and the satellite snow depth data set. The variograms for the SSM/I and gauge SD estimates for each of the 10 days show a broad similarity with respect the mean estimated snow depths for each year. For example, the nugget variance increases with increasing mean snow depth for both data sets suggesting that representation of micro-scale effects of snow distribution is not possible for thicker snowpacks. The range decreases with increased mean snow depth in both gauge and SSM/I data sets also suggesting that snow depth variability is smaller over short distances only when the snow is thick. For shallower snowpacks, the spatial variability is small over comparatively larger distances.

With respect to differences in variogram structure between gauged and satellite derived snow depth data, four variogram pairs (SSM/I estimated and gauge measured) have range differences less than 200 km, one pair has a range difference between 200 and 300 km, two have differences between 300 and 400 km and one pair has a difference between 400 and 500 km. Furthermore, applying the paired t-test to the SSM/I and gauge variogram range data in Table 2 gives a $|t|$ value of 0.13 and the critical t value for a sample of 8 is 2.37. These results suggest that there is some agreement between the spatial variability of SD estimated from the SSM/I retrievals and gauge measurements.

(3) Error analysis and determination of the required sampling characteristics of snow gauge measurements

Before determining how many snow gauges are needed to achieve a specified SD areal accuracy, it is necessary to understand the error characteristics of satellite-derived SD estimates and gauge SD measurements. Data from both SD sources are subject to systematic and non-systematic or random errors. For snow gauge SD measurements, there might be both systematic and random errors associated with each measurement. Systematic errors from gauge measurement data are attributed to the situation of the ruler and its representativity of the local conditions (Goodison *et al.* 1981). Ideally, several measurements are needed to produce a representative sample but such information is usually not available in the cooperative data archive so that inferences about gauge systematic errors cannot be made. For satellite SD estimates, both systematic and random errors are associated with the retrieval algorithm and are referred to as retrieval errors (Bell *et al.* 1990). Systematic biases are known to exist in relation to vegetation cover and snowpack parameterization of the algorithms. While the quantification of these errors is the focus of ongoing studies (for example, see Derksen *et al.* 2003), in general, the error biases are consistent. For the satellite SD estimates, therefore, we assume a constant systematic error because the study location and the study date each year are constant. In this study, therefore, the error term in both data sets that we use to determine the accuracy achievable from a predefined number of gauges is the random error term of the total error.

A technique for estimating the random error of rainfall estimates, described in Chang *et al.* (1993) requires a pair of independent variables (*i.e.* rain gauge measurements and satellite estimates). Applying their methodology to snow depth retrievals, gauge SD estimates and satellite SD estimates are denoted as g and s respectively and it is assumed that there are random errors associated with these estimates. Thus, we can write

$$\begin{aligned} g &= \langle g \rangle + e_g \quad \text{cm} \\ s &= \langle s \rangle + e_s \quad \text{cm} \end{aligned} \tag{4}$$

where < > represent ensemble averaging taking over different number of gauge categories, and e_g and e_s are the random errors associated with independent SD estimates of the gauge and satellite variables. Assuming that the estimates are unbiased with uncorrelated errors,

$$\begin{aligned} \langle e_g \rangle = \langle e_s \rangle = 0 \quad \text{and} \\ \langle e_g \, e_s \rangle = 0. \end{aligned} \tag{5}$$

The error terms e_g and e_s contain errors due to gauge sampling and satellite retrievals from the ensemble averaging. We can express the mean square difference of gauge estimates and satellite estimates as

$$\langle (g - s)^2 \rangle = (\langle g \rangle - \langle s \rangle)^2 + \langle (e_g - e_s)^2 \rangle \quad \text{cm}^2. \tag{6}$$

Equation (6) states the mean square difference between the gauge SD and satellite SD estimates is the variance due to the random error.

For the ten-year data set (1988 to 1997), 1° x 1° grid cells (approximately 10^4 km^2) were used as the study framework to investigate the random errors. All grid cells were classified according to the number of gauges within the cell, a measure of the spatial density of gauges. The frequency distribution of gauges per cell varied from one gauge to 10 gauges per cell and is plotted in Figure 3. The most frequent category was 3 gauges per cell (159 cells). Typically 22 SSM/I SD retrieval points were located within each 1° x 1° grid cell.

Table 3 shows the number of cells with n gauges, the mean and standard deviation of gauge SD and satellite SD, the mean difference between the gauge SD and satellite SD (mean difference = $< g > - < s >$) and the standard deviation of the differences, the root-mean-square of the difference (RMSD) between gauge and satellite SD (RMSD = $< (g - s)^2 >^{1/2}$) and the total error can be written as

$$< e^2 >^{1/2} = [< e_g^{\ 2} > + < e_s^{\ 2} >]^{1/2} \tag{7}$$

The paired t-statistic of the means was also computed.

Overall, the mean difference and RMSD between gauge and satellite SD was 1.1 cm and 16.1 cm, respectively. The mean difference between gauge SD and SSM/I SD for each category is relatively small. From the paired t-test, none of the $|t|$ values was greater than 1.96 suggesting there was no significance difference between the mean gauge and satellite SD estimates. Additionally, the standard deviation of the mean difference (16.1 cm) is about the same as the mean of satellite and gauge SD for each category (18.2 cm). An important characteristic of these data is that the RMSD decreases as the number of gauges per cell increases suggesting that the number of gauges within a box might influence estimated random error. The total error decreases from 20.4 cm for one gauge per cell to 10.0 cm at 9 gauges per cell supporting the possibility that the number of gauges might influence the estimated error.

The number of point measurements needed to represent a physical parameter within a pre-defined error range depends on the spatial variability within the area and the accuracy requirements. For precipitation studies, there have been several studies that addressed the sampling errors of the spatial variance of precipitation. In precipitation estimates, Bell *et al.* (1990) reports that sampling error dominates the total error. Bell *et al.* (1990), Huffman (1997) and Chang and Chiu (1999) reported that the relationship between sample error of spatial variance (ε) and the number of samples is of the form $\varepsilon^2 \sim 1/n$ for precipitation. Rudolf *et al.* (1994) reported a similar error estimation relationship of the form $\varepsilon^2 \sim 1/n^{1.11}$ in a 2.5° x 2.5° grid domain of gauge precipitation data. In this snow study, we attempt to determine the number of samples required for SD estimates at a 1° x 1° grid domain within a limit of sampling error ε. To be 95% confident that the true mean is within $\pm\ \varepsilon$ of the observed mean, the number of samples (n) required is

$$\varepsilon^2 = (1.96\sigma)^2 / n \approx 4\sigma^2/\mathrm{n} \qquad (8)$$

where σ is the standard deviation of the variable (Snedecor and Cochran 1967).

From Eq. 7, the total error $< e^2 >^{1/2}$ can be calculated by the square root of the sum of gauge error $< e_g{}^2 >$ and satellite error $< e_s{}^2 >$. The gauge mean error is dominated by gauge sample configuration, especially the gauge spatial density. The satellite error is caused by algorithm error and is not directly related to the gauge spatial density. Since the snowfield of the NGP area is rather uniform (relatively homogeneous low stand vegetation and snowpack properties), it is possible to make the assumption that the satellite algorithm error is probably about the same for all grid cells. By adjusting the e_s and optimizing the fit using the least squares criterion of e_g^2 in proportion to 1/n, then e_s and e_g can be individually estimated. The calculated e_s is 8.8 cm and $e_g^2 = 466.7/n$. Figure 4 shows the estimated sampling error for different numbers of gauges per grid cell. The gauge error varies from about 20 cm for one gauge per grid cell and decreases to 7 cm for ten gauges per cell. In other words, in order to achieve 5 cm accuracy more than 10 gauges within a grid cell are required. This is an important outcome since it defines a limitation to the error characteristic as a function of the gauge spatial density at this grid cell scale (*i.e.* 1° x 1° of latitude and longitude).

V Summary and Discussion

Ten years of gauge SD data were used to evaluate the single SSM/I footprint derived SD for Northern Great Plains snowfields. From year to year comparisons, seven out of ten years had significant differences between gauge and SSM/I SD estimates. The mean gauge SD for ten years composite was 17.2 cm with a standard deviation 21.7 cm, while the SSM/I estimated SD was 17.4 cm with a standard deviation of 17.4 cm. The ten years mean difference between gauge SD and SSM/I estimated SD was 0.2 cm, which is not statistically significant.

The variograms of gauge and SSM/I derived SD estimates were comparable. The ranges of gauge and SSM/I vary within of 500 km of each other. In general, the ranges decreased as the snow depth increased suggesting that for thinner snow packs, the correlation lengths increase while for thicker snowpacks they decrease. Also, the nugget variances were larger for thicker snowpacks suggesting that there is more unresolved variation at each sample point when greater snow accumulations are present.

Comparisons of the 1° x 1° latitude-longitude gridded data showed that the yearly differences of gauge SD and SMM/I SD were not significant. The ten-year composite mean and standard deviation of the gauge SD was 17.7 cm and 19.7 cm respectively, and the SSM/I estimated SD was 18.8 cm and 16.9 cm, respectively. The mean difference gauge and satellite estimate of SD was 1.1 cm and was not significant. The standard deviation of the difference between gauge and SSM/I SD was slightly smaller (16.1 cm) than the comparison for point data.

This research suggests that the SSM/I data can be used effectively to map snow depth in the NGP area. Snow depth spatial variability can be captured by the SSM/I retrieved snow depth that has a calculated error of 8.8 cm. In comparing the SSM/I estimates with gauge estimates, the advantage of increasing the number of gauges within a grid cell is reported. The sampling error of gauge SD is about 20 cm for one gauge, 7 cm for 10 gauges and more than 10 gauges for less than 7 cm on a 1° x 1° grid cell domain. However, the characteristic curve relating estimation error with number of gauges per cell curve shows that for the Northern Great Plains area, greater than 10 gauges per cell, the sampling error does not reduce quickly. In the context of global snow depth estimates, this research demonstrates that it is rather difficult to quantify the global SD accuracy by using only the limited snow gauge data where gauge density is often less than one gauge per 1° x 1° of latitude and longitude.

The Advanced Microwave Scanning Radiometer (AMSR) was launched on-board the Japanese Advanced Earth Observing Satellite-II (ADEOS-II) and the United States Earth Observation System (EOS) Aqua satellite in 2002. AMSR can provide the best ever spatial resolution multi-frequency passive microwave radiometer observations from space (18 GHz channel instantaneous field of view (IFOV) is 27 km x 16 km and 36 GHz channel IFOV is 14 km x 8 km). This capability provides us with an opportunity to estimate surface snow mass quantities at finer spatial resolutions than have been possible on previous missions and so represents an opportunity to improve snow depth observations both with respect to spatial resolution and accuracy of retrieval. However, for field experiments designed to test satellite observations, the ground sampling network requires careful planning to ensure snow cover parameters such as SD are accurately measured.

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Figure 1: Location of the snow gauge collection points within the Northern Great Plains study region.

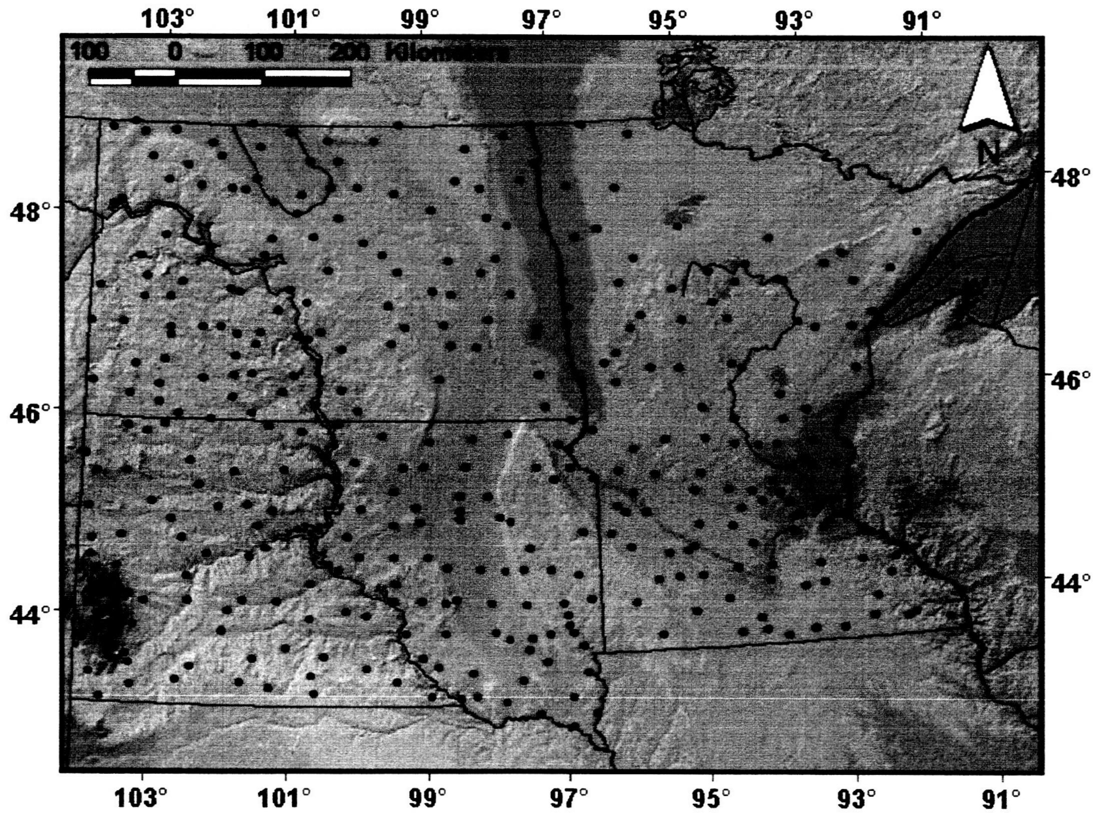
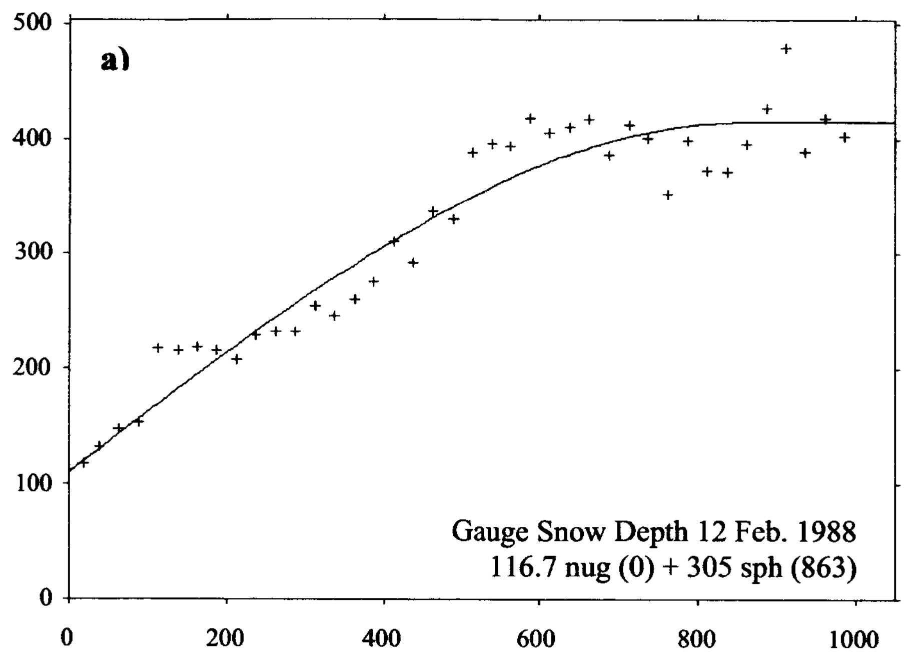


Figure 2: Variograms of: a) gauge measurements of snow depth, and b) SSM/I estimates of snow depth for the Red River basin for 12 February, 1988.



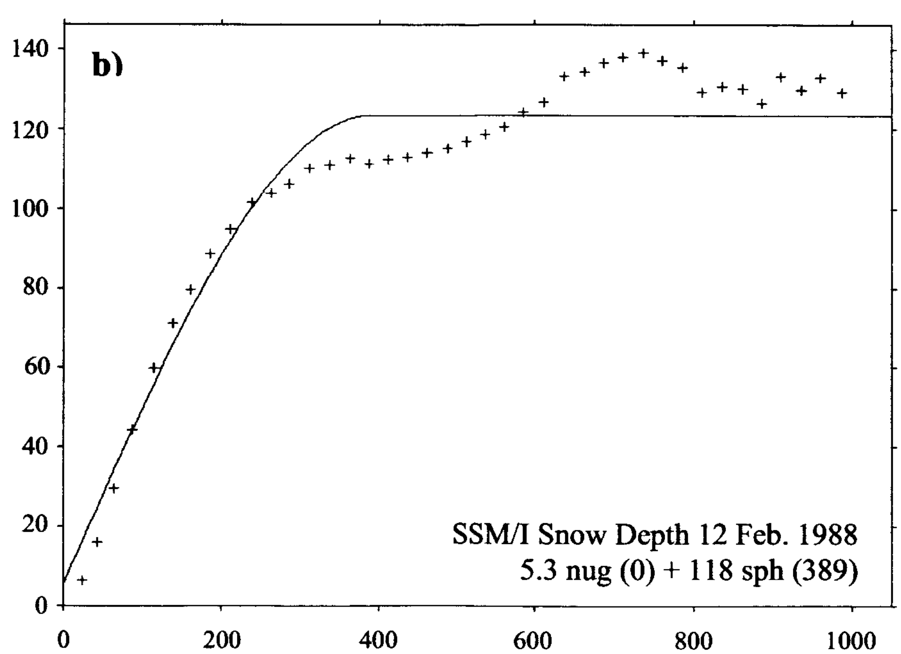


Figure 3: Frequency distribution of number of gauges per cell

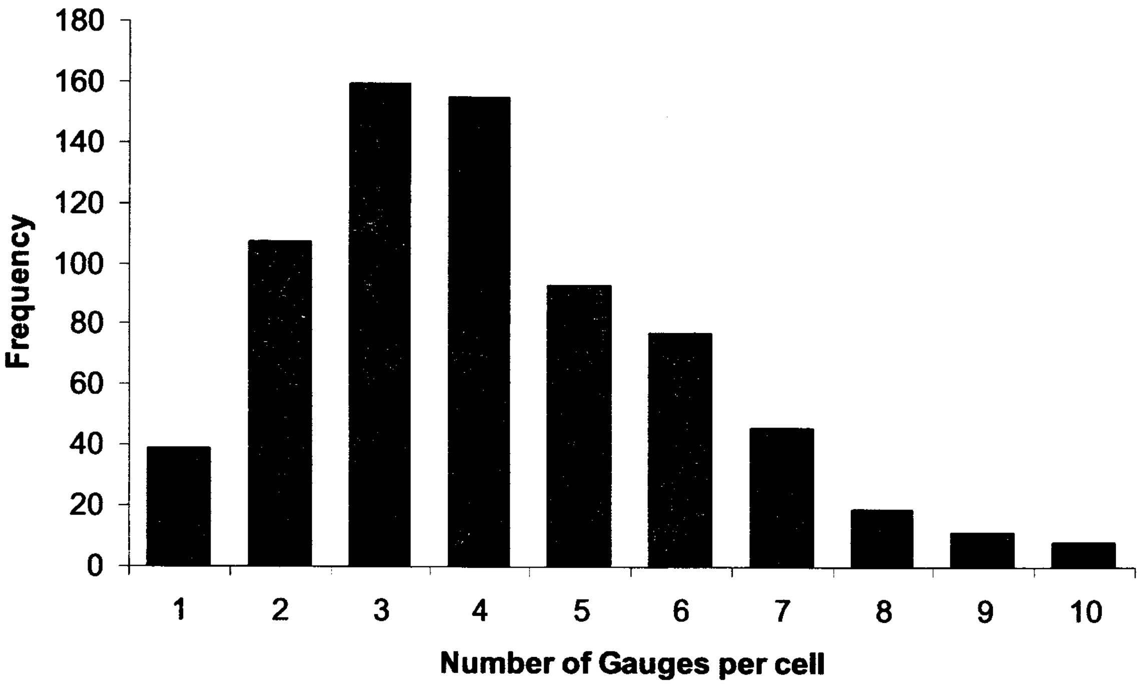


Figure 4: Estimated gauge SD error vs. number of gauges.

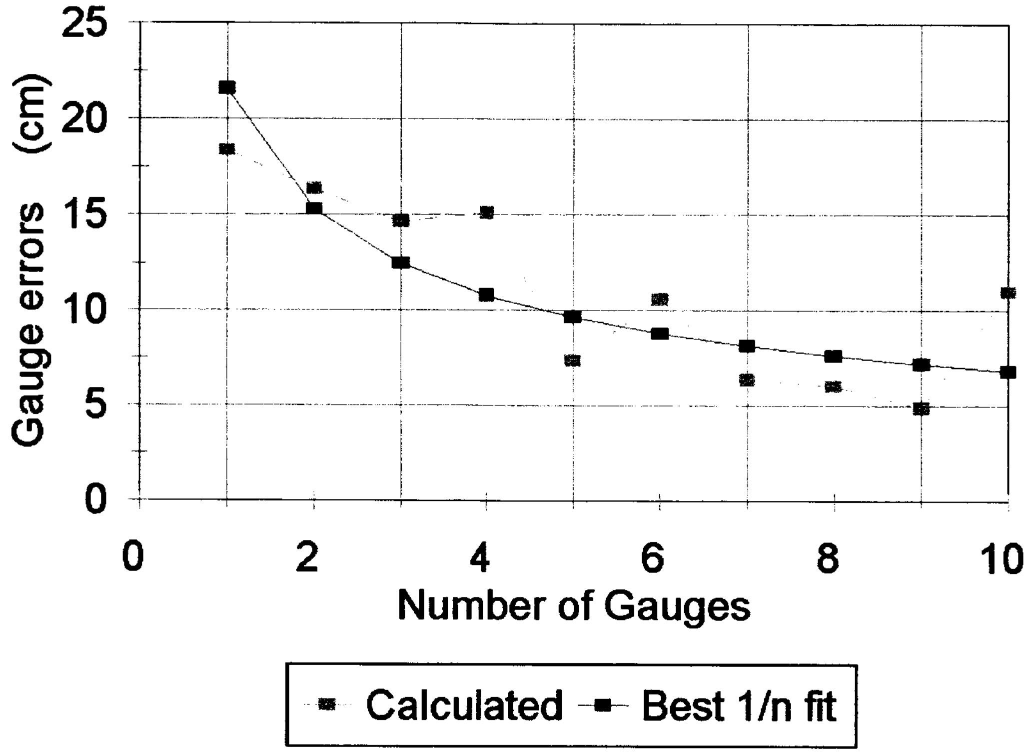


Table 1: Ten years of mean (μ) and standard deviation (σ) of gauge and SSM/I snow depth estimates and the paired *t*-test values.

Year	N Pairs	Gauge μ (cm)	Gauge σ (cm)	SSM/I μ (cm)	SSM/I σ (cm)	Paired t-value
1988	256	23.1	17.1	19.5	11.6	4.04
1989	265	16.3	19.0	14.3	11.6	2.24
1990	339	1.8	5.6	1.7	4.2	0.68
1991	351	1.5	4.1	4.4	11.3	-5.57
1992	281	6.7	9.5	7.8	11.8	-1.99
1993	269	19.5	11.0	29.4	15.5	-9.45
1994	266	39.1	19.3	20.7	10.5	18.02
1995	271	10.3	12.2	22.7	19.5	-12.15
1996	302	18.0	23.0	18.1	13.5	-0.05
1997	275	45.4	29.9	43.4	13.8	0.96
1988-1997	2875	17.2	21.7	17.4	17.4	0.26

Table 2 Variogram characteristics of gauge and SSM/I-retrieved snow depth data

	Gauge Data			SSM/I Data			Difference
Year	Gauge μ (cm)	Range, a (km)	Nugget, c_0 (cm^2)	SSM/I μ (cm)	Range, a (km)	Nugget, c_0 (cm^2)	Absolute Range Difference (km)
1988	23.1	863	116.0	19.5	389	5.3	474
1989	16.3	836	1.0	14.3	595	2.5	241
1990	1.8	N/A	N/A	1.7	952	2.0	N/A
1991	1.5	N/A	N/A	4.4	1040	3.4	N/A
1992	6.7	459	3.3	7.8	776	5.0	317
1993	19.5	727	61.8	29.4	667	0.0	60
1994	39.1	464	161.3	20.7	533	0.8	69
1995	10.3	756	7.3	22.7	563	2.1	193
1996	18.0	645	54.1	18.1	793	14.1	148
1997	45.4	334	245.8	43.4	662	24.5	328

Table 3: The number of cells, mean and standard deviation of gauge SD and SSM/I SD estimates, mean difference between gauge and SSM/I SD estimates and the standard deviation of these differences, RMSD between the gauge and SSM/I SD estimates, the non-systematic errors of gauge and SSM/I SD and paired *t*-test value between gauge and SSM/I SD for each gauge category.

Category: N gauges per cell	**Number of cells**	**Gauge SD mean (cm)**	**Gauge SD standard dev. (cm)**	**SSM/I SD mean (cm)**	**SSM/I SD standard dev. (cm)**	**Diff. in gauge and SSM/I means (cm)**	**Standard dev. of mean diff. (cm)**	**RMSD (cm)**	**Total Error (cm)**	**Paired *t*-value**
1	39	24.6	19.5	19.1	15.6	-5.5	20.7	21.2	20.4	-1.67
2	107	21.1	20.9	21.9	16.2	0.7	18.7	18.6	18.6	0.38
3	159	22.3	21.2	22.2	17.3	-0.02	17.1	17.1	17.1	-0.02
4	155	18.5	19.7	20.4	16.7	1.9	17.6	17.7	17.5	1.34
5	93	13.3	18.0	15.4	16.7	2.1	11.6	11.7	11.5	1.74
6	77	13.3	17.1	16.3	18.0	3.0	13.8	14.1	13.8	1.91
7	46	8.6	15.8	9.6	15.3	1.0	11.0	11.0	10.9	0.60
8	19	11.0	13.4	14.6	12.8	3.6	11.0	11.3	10.7	1.43
9	11	13.1	14.6	14.7	15.3	1.6	10.5	10.1	10.0	0.52
10	8	20.1	17.2	24.8	15.0	4.7	15.1	14.9	14.1	0.88
Total	**724**	**17.7**	**19.7**	**18.8**	**16.9**	**1.1**	**16.1**	**16.1**	**16.1**	**1.77**